Real-time wet/dry road surface discrimination using rolling noise acoustic footprint analysis

Jesús Alonso, Juan Manuel López, Ignacio Pavón, César Asensio, Guillermo de Arcas
Instrumentation and Applied Acoustics Research Group (I2A2), Universidad Politécnica de Madrid (UPM).Campus Sur, Crta. de Valencia km. 7, 28031 Madrid, Spain.
email: jesus.alonsof@upm.es

Road surface changes due to the weather conditions have a major influence in driving safety. To avoid accidents, drivers must adapt their driving style according to the road status. This adaptation mechanism depends on the driver ability to detect the pavement conditions. Unfortunately, this is often a difficult task. A system capable of notifying the driver about changes on the road surface due to weather aspects, could improve this adaptation mechanism, thus reducing accident risk. An electronic system capable of estimating the road surface status between dry and wet status is presented. The system is mainly based on the analysis of the tyre/road noise generated during driving. The sound emission pattern of the tyre/road interaction changes depending on whether the pavement is dry or wet. Thus discriminating the tyre/road noise acoustic footprint, it is possible to estimate the road status. Proposed system captures and digitizes tyre/road noise. Rolling noise is pre-processed extracting its spectral components to construct the feature vectors. Feature vectors are processed by a Support Vector Machine (SVM) based classifier. Then the classifier outputs the road surface status estimation. The first implementation of the system, using Matlab along with pre-recorded tyre/road noise, shows high success rates (around 91 %). These promising results are leading to the development of a hardware prototype, tightly integrated with the vehicle, and capable of computing the classification algorithms in real time.

---

1. Introduction

One of the main problems in the terrestrial transportation sector is the occurrence of accidents. Usually, accidents are the result of a combination of several factors, including limitations in vehicle dynamics and human errors. Ultimately, it is reasonable to argue that driver errors are the most important, because a good driver can countervail to a great extent the problems arisen due to vehicle limitations and environmental challenges.

A driver traversing a wet, icy or snowy road, must adapt his driving style accordingly, reducing the speed and increasing alertness. Unfortunately, even a careful driver can get caught in dangerous situations. It is difficult to estimate the depth of eventual water formations that could lead to *aqua-planing*. Very thin and slippery *black ice* layers can appear on the road in very localized areas. Also the psychological *anchoring effect* [1] can make really difficult for a driver to notice adverse changes in weather during a travel. In these cases, it is vital to inform the driver about these adverse road conditions, and as soon as possible. An on-board system capable of accurately estimating the presence

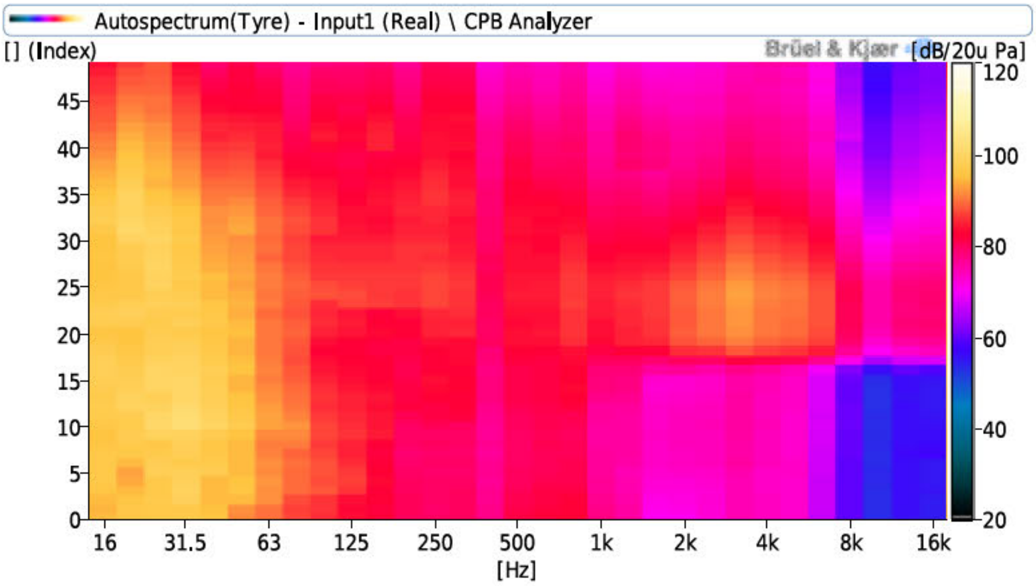


Figure 1: Unweighted tyre/road noise obtained during a dry/wet/dry transition.

of water, ice and snow on the road could provide valuable information to the driver and also to other electronic vehicle subsystems, increasing driving safety.

There have been several approaches trying to address this problem, by providing an automatic means of detecting alterations on the road surface. Sometimes, proposed systems cannot be integrated on-board (e.g. the ones based on radar technology [2]). Other approaches can operate in vehicle, but have low success rates (e.g. the ones based on image analysis [3]) or require complex and expensive installations (like the one developed in the IcOR project [4]). For the system to be widely accepted by the automotive industry, it is necessary to achieve a high success rate, with a cheap and easy to install system.

In this paper a system capable of detecting the presence of water on the asphalt is presented. The system is based on the acoustic analysis of rolling noise, achieving a high success rate. It is also easy to install and avoids using expensive transducers, demonstrating that cheap electret microphones are suited for this task.

2. Principle of operation

Noise generated by motor vehicles can be grouped into three categories: wind turbulence noise, power unit noise and tyre/road noise. Tyre/road noise is generated during the displacement of the car, due to the complex interaction of the tyre and the road surface. On modern automobiles, it poses the greatest contribution to vehicle noise, at least for legal speeds greater than $40\,\mathrm{km\,h^{-1}}$. Although the acoustic footprint of the generated tyre/road noise, depends on a lot of factors (including the tyre type, asphalt type, speed, wheel inflation pressure, etc.), the generated noise while driving on dry asphalt is easily distinguishable of the one generated by a tyre rolling on a wet road, as can be seen in figure 1, which shows the unweighted ⅓ octave bands while the test car, initially over dry aspahlt, traverses a wet asphalt section (the Y axis shows the time in $1/8$ s increments). In general terms, when a vehicle traversing a dry road crosses a wet section, two effects are observed [5]:

- Sound pressure level increases for frequencies greater than 1 kHz.
- Sound pressure level decreases for frequencies lower than 1 kHz.

This allows to discriminate the road status by analysing the tyre/road noise acoustic footprint.

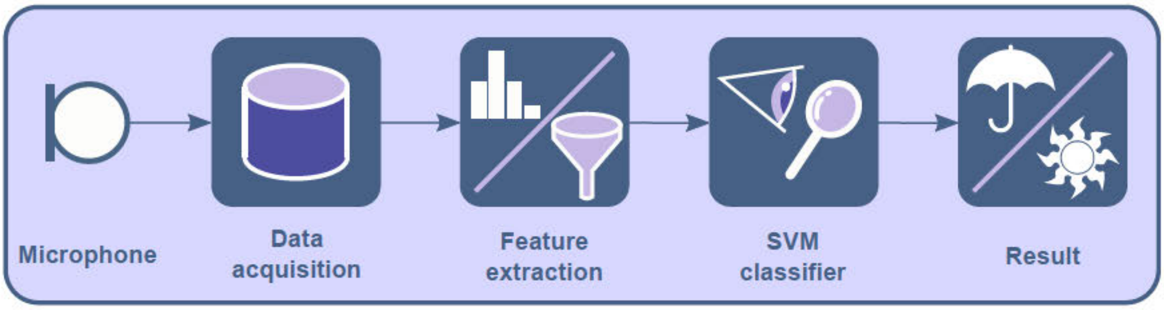


Figure 2: System architecture

3. System architecture

In order to be able to discriminate the road status by analysing the rolling noise, a pattern recognition algorithm must be used. Developed system incorporates a Support Vector Machine (SVM) based classifier. The architecture of the system is shown in figure 2. A *Microphone* close to a wheel captures the rolling noise. The weak electrical signal output by the microphone is amplified and digitized by the *Data acquisition* block. Then the digital signal is processed by the *Feature extraction* block, to obtain its relevant spectral components. Then the feature vector is output and processed by a SVM classifier, that will compute a road state estimation.

One of the key elements when developing classifiers, is to carefully select the optimum features that carry the information needed by the classifier to output accurate estimations. As the acoustic footprint information is contained in the spectral components of the signal, to obtain the feature vector, some kind of spectral estimation algorithm must be used. Tests have been made with feature vectors computed using both FFT and ⅓ octave filters. These test have proved that feature vectors elaborated by computing the energy obtained inside the ⅓ octave frequency bands obtain better results.

Support Vector Machines are supervised classifiers, thus before the classifier can operate, it has to be properly trained. The training stage serves two purposes:

- Dimensionality of the feature vector is reduced, by performing a feature selection. This decreases the computing power needed by the classifier, and increases generalization performance.
- The Support Vectors are computed. This allows to obtain the optimum decision function leading to the greatest class margin.

To select the ⅓ octave bands maximizing the classifier performance and minimizing required computing power, feature selection algorithms RFE (*Recursive Feature Elimination*) [6] and L0 (*Zero-norm minimization*) [7] have been used.

4. Feature extraction and selection

As stated on section 3, features vectors are computed by obtaining the energy contained in the ⅓ octave bands of the captured rolling noise. This is shown on figure 3. Captured tyre/road noise samples are grouped in segments of 125 ms by the *Temporal Windowing* block. Then each block is analysed. On one hand, the energy contained in the whole block is computed. On the other hand, the energy contained into each ⅓ octave band is obtained. Then the energy obtained for each ⅓ octave band is normalized. This adds an important advantage to the system: it minimizes the influence of the variations in the global sensitivity of the microphone. These sensitivity fluctuations often appear due to several factors (e.g. aging, temperature and humidity variations, etc.).

Initially, the feature vector is comprised of the normalized energy of the 30 one third octave bands from 25 Hz to 20 kHz. During the feature selection, most of these features are discarded. Feature selection minimizes the computing power required to estimate a result. This is important because the system is intended to work in real-time. But dimensionality reduction in these kind of classifiers has

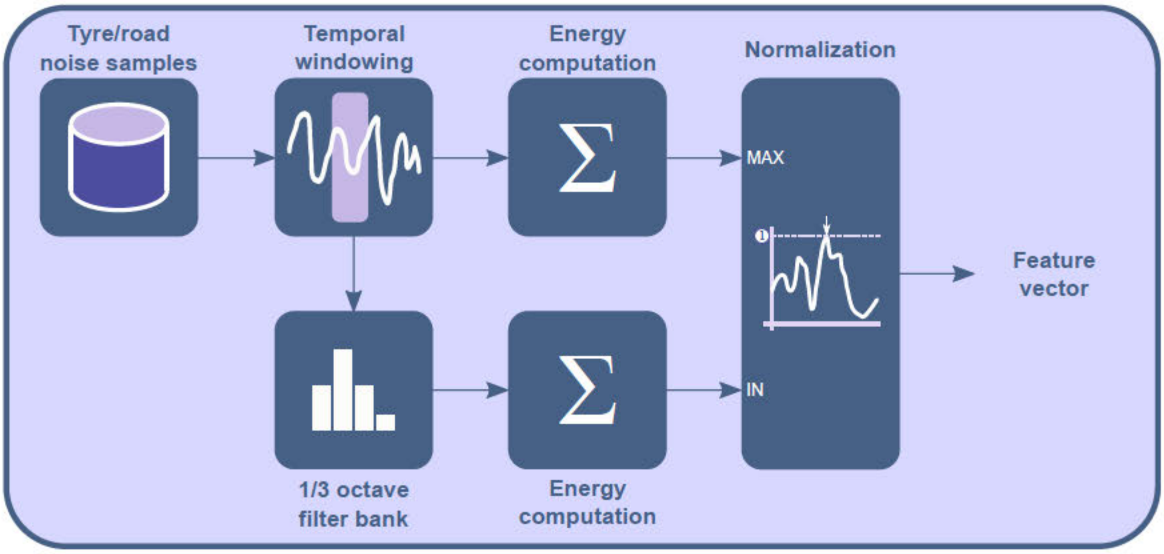


Figure 3: Blocks comprising the Feature Extraction stage.

another important advantage, it usually enhances generalization performance [8].

5. Training and tuning

The classifier has been trained using a training set comprising 232 feature vectors. This training set was obtained by recording the tyre/road noise generated by a test vehicle while driving approximately at $50\,\mathrm{km\,h^{-1}}$ on a closed circuit. First the rolling noise while asphalt was dry was recorded. Then a section of the circuit was constantly watered, to allow the recording of the tyre/road noise on wet asphalt.

The equipment used to record the audio data was composed of a *Panasonic WM-63PR* electret microphone connected to a *Bruel & Kjær Pulse* front-end. Using a cheap electret microphone tries to prove that a high quality microphone is not required for the classifier to produce reliable results. This is partially because the training process can compensate deviations of the microphone frequency response from the ideal flat one. Also near to the tyre, sound pressure levels captured while driving are high, so a high sensitivity microphone is not required.

The audio tracks stored during the training session, were separated and assigned to their corresponding class (wet/dry) for the training algorithm to be able to compute the support vectors. Once the classifier was trained, several additional tyre/road noise recording sessions were performed on the same track, to obtain a test set. Recordings were made on different days, and the recording equipment was dismounted and mounted again on test car on each session, to introduce systematic errors, allowing to further test the robustness of the classifier. Obtained test set comprises 209 920 feature vectors.

Preliminary results obtained with the trained system showed that it was error prone when driving on dry asphalt at speeds lower than $30\,\mathrm{km\,h^{-1}}$. There are two possible explanations to this phenomenon:

- The system was trained at $50\,\mathrm{km\,h^{-1}}$, so its performance may degrade as we get farther from this speed (although it is important to remark that for speeds greater than $50\,\mathrm{km\,h^{-1}}$ this problem does not appear).
- The signal to noise ratio (considering as signal the tyre/road noise, and as noise any other sound captured by the microphone) degrades as the vehicle speed lowers. Low signal to noise ratios can lead to degraded system performance.

Another problem found during the initial tests, is that as the feature vectors are obtained by computing the energy of the signal on very short time intervals (i.e. 125 ms), spurious acoustic events

Table 1: Features selected by RFE and L0 algorithms.

Selection algorithm	Center frequency of the 1/3 octave band for each feature (Hz) 1	2	3	4	5	6	7	8	9	10
RFE	5000	1600	630	250	160	4000	3150	40	1250	1000
L0	5000	1600	630	200	250	8000	40	3150	16000	20000

produced e.g. by pebbles hitting the microphone surroundings can cause wrong classifications.

To avoid these problems, a filter stage has been added after the classifier. This filter does not change its output unless there have been N equal and consecutive events at the output of the classifier, thus avoiding that spurious events of short duration may cause wrong results. Unfortunately, adding this filter increases the response time of the system. A value of N = 8, increases the system performance while maintaining a fast response time.

To enhance the system performance at speeds lower than $30\,\mathrm{km\,h^{-1}}$, the filter block also inhibits transitions on its output when driving at these speeds. It is expected that this workaround does not have a negative impact on safety, because the probability of losing control of the vehicle because of the presence of water on the road is really low at speeds lower than $30\,\mathrm{km\,h^{-1}}$.

6. Results and discussion

Figure 4 shows the hit rates obtained by the classifier, for the detection of wet and dry surfaces, while using feature vectors with a number of features ranging from 1 to 10. The data is shown for features selected by the RFE algorithm (4a) and for the features selected by the L0 algorithm (4b). Table 1 lists the center frequencies of the ⅓ octave filters corresponding to the features obtained by the selection algorithms. The results show that wet asphalt is always detected, achieving a 100 % success rate. Dry asphalt is not always properly detected, but hit rate is very high (higher than 90 %, excepting when using only one feature). Hit rate depends on the number of features selected, and as was discussed in section 4, decreasing the dimensionality of the feature vector up to a critical value, tends to enhance generalization performance. The greatest hit rate is obtained when using feature vectors composed of 4 features selected by the L0 algorithm. In this case, center frequencies selected for the ⅓ octave filters are: 5 kHz, 1.6 kHz, 630 Hz and 200 Hz. Selected frequencies reflect both effects highlighted by Descornet [5] about tyre/road noise on wet asphalt:

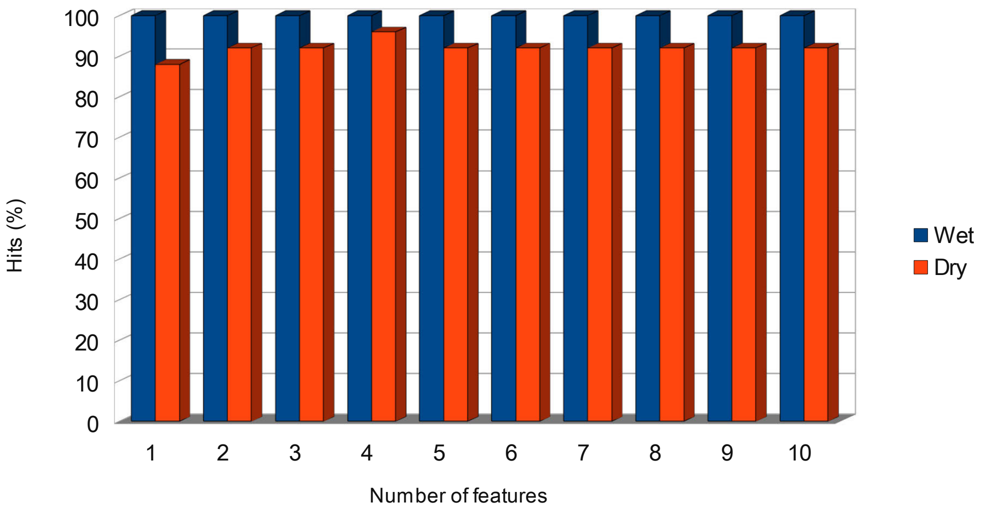
1. Noise level increases in the high and medium frequencies due to the spray of water droplets.
2. Noise level decreases in the low and medium frequencies due to an unknown phenomenon.

A real time DSP-based implementation of the system has been developed, showing no performance degradation, and obtaining very short response times. Using this implementation, a subjective evaluation of the system in real driving conditions has been made. Drivers have perceived the accuracy of the system as very high, and the response time as almost instantaneous.

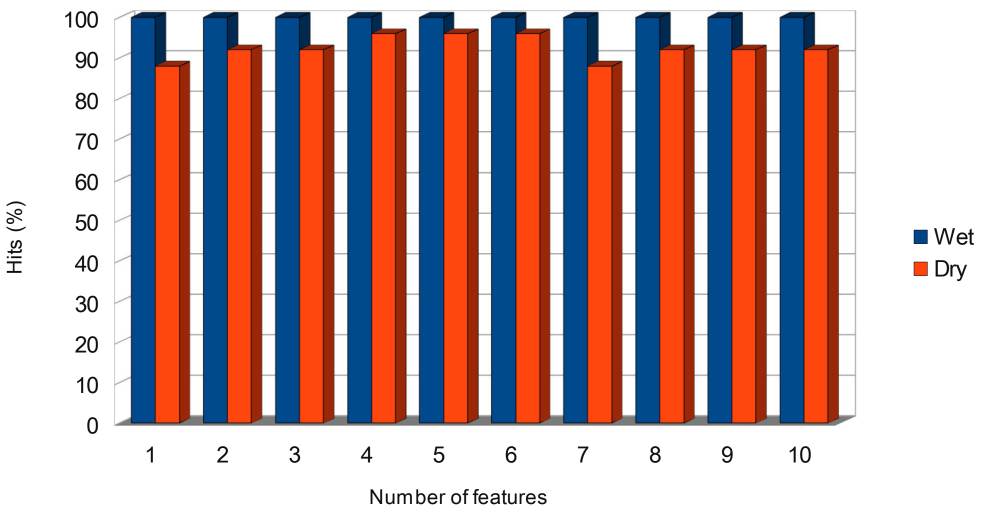
Another real time implementation based on a general purpose microcontroller is actually under development. This implementation is focused mainly on two objectives:

– Integrating the system with the Engine Control Units (ECUs) of the motor vehicles. This is achieved by adding an interface capable of communicating with the ECUs.
– Minimizing size and cost of the system.

Integrating the system with the vehicle ECUs, allows it to obtain vehicle dynamics (e.g. speed and RPM) directly measured by the vehicle sensors. Also the estimation results can be sent to the vehicle console (to inform the driver) and to other ECUs. Using this data, vehicle traction control systems could further enhance safety. Also cutting system cost is important because this kind of systems are only adopted by vehicle manufacturers when their cost is low enough.



(a) Results using RFE selected features.



(b) Results using L0 selected features.

Figure 4: Hit rates for the detection of dry and wet roads, depending on the number of features and the selection algorithm.

REFERENCES

1. Einhorn, H.J. and Hogarth, R.M., *A Theory of Diagnostic Inference. I. Imagination and the Psychophysics of Evidence*, Center for Decision Research, Graduate School of Business, University of Chicago, (1982).

2. Viikari, V., Varpula, T. and Kantanen, M., Road-Condition Recognition Using 24-GHz Automotive Radar, *IEEE transactions on intelligent transportation systems*, **10** (4), 639–648, (2009).

3. Yamada, M., Oshima, T., Ueda, K., Horiba, I. and Yamamoto, S., A study of the road surface condition detection technique for deployment on a vehicle, *JSAE Review*, **24** (2), 65–71, (2010).

4. Jokela, M., Kutila, M. and Le, L., Road condition monitoring system based on a stereo camera, *IEEE 5th International Conference on Intelligent Computer Communication and Processing*, Cluj-Napoca, Romania, 27–29 August, (2009).

5. Descornet, G., Vehicle noise emission on wet road surfaces, *Proceedings of the 29th International Congress on Noise Control Engineering*, Nice, France, (2000).

6. Guyon, I., Weston, J., Barnhill, S. and Vapnik, V., Gene selection for cancer classification using support vector machines, *Machine Learning*, **46** (1), 389–422, (2002).

7. Weston, J., Elisseeff, A., Schölkopf, B. and Tipping, M., Use of the zero norm with linear models and kernel methods, *The Journal of Machine Learning Research*, **3**, 1439–1461, (2003).

8. Jain, A.K., Duin, P.W. and Jianchang, M., Statistical pattern recognition: A review, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **22** (1), 4–37, (2000).